

UNITED STATES PATENT APPLICATION

OF

ALI SAZEGARI

and

DOUG CLARKE

FOR

**SINGLE-CHANNEL CONVOLUTION IN A
VECTOR PROCESSING COMPUTER SYSTEM**

Attorney Docket No. P2395-514
Burns, Doane, Swecker & Mathis, L.L.P.
Post Office Box 1404
Alexandria, Virginia 22313-1404
(703) 836-6620

099687 113001

SINGLE-CHANNEL CONVOLUTION IN A VECTOR PROCESSING COMPUTER SYSTEM

FIELD OF THE INVENTION

[0001] The present invention relates generally to signal processing within a computer processor. More particularly, the present invention relates to convolution operations in a vector processing computer system.

BACKGROUND OF THE INVENTION

[0002] One of the most important, value-adding features in a computer is its ability to process large amounts of data and information. Some of the information frequently processed by a computer includes image and other signal information. Frequently, information processed on a computer may relate to the general computer display, computer graphics, scanned images, video, and other data. With each of these types of data, it is often desirable to utilize the convolution function to process the data.

[0003] Convolution is useful in demonstrating the manner in which two signals interact in the time domain, and in expressing a resulting signal from the mixing of the two signals within the time domain. Mathematically, convolution is the multiplication of two sequences, which can be expressed in the form of an integral shown below in equation 1.

$$y(t) = f(t) \otimes g(t) \equiv \int_{-\infty}^{\infty} f(\tau)g(t-\tau)d\tau \quad (1)$$

[0004] In Equation 1, two signals $f(t)$ and $g(t)$ are convolved to yield the resulting signal $y(t)$. The far right side of Equation 1 shows the general convolution integral wherein the signals are expressed in terms of τ and $t-\tau$, as a sliding function. This convolution integral exhibits various useful properties. For example, the convolution operation is commutative, distributive, and associative

and allows shifting of the resulting $y(t)$ by the same amount as the input signals $f(t)$ and $g(t)$. The width along the t -axis of the resulting signal $y(t)$ is the combined width of the two input signals $f(t)$ and $g(t)$.

[0005] Convolution may also be performed using a digital or discrete method. In this manner, the convolution integral is expressed as a convolution sum. Equation 2 below shows a general convolution sum.

$$y[k] = f[k] \otimes g[k] = \lim_{T \rightarrow 0} \sum_{m=-\infty}^{\infty} f[m]g[k-m] \quad (2)$$

This convolution sum is the discrete-time equivalent of the convolution integral shown in Equation 1. In Equation 2, two discrete input signals $f[k]$ and $g[k]$ are convolved using the convolution sum to obtain the resulting signal $y[k]$. One of the signals is reflected about the y -axis and translated over the entire range of values of m (in this case the width of $g[k]$), whereupon the values of the two signals are multiplied together at each commonly shared discrete location and the products of each value of m are summed. T represents the sampling frequency, or sampling interval. This is the interval at which samples of the continuous functions are taken and corresponds to the spacing between discrete values of the discrete functions. Using the discrete convolution sum allows a computer to perform discrete convolution calculation.

[0006] One of the main problems in performing convolution using a computer is that the process is inherently linear. For relatively long sequences, therefore, the convolution process can be quite lengthy. Generally, a computer reads each function to be convolved as a stream of data, one element at a time. This requires valuable processor time, and the time required increases proportionately to the complexity and length of the signals to be processed. This is especially problematic, for example, in image processing applications and/or video applications, where signals are complex and memory-intensive. In video

09996877-113001

[0007] As processor speeds and users' demands for quality increase, it is essential that signals which are processed by way of a convolution sum, such as the one shown in Equation 2, are processed in the most efficient manner without sacrificing quality. Even with the increased processor speeds of today, performing convolution as a serial process whereby entire streams of data are input, output, and computed sequentially, slows a computer's ability to process signals and information, and generally slows the processing of data involved in unrelated functions by the computer.

[0008] Recently, vector processing, which utilizes parallel computing operations, has been implemented in various computer systems. This type of computer processing has the advantage that multiple calculations may be performed simultaneously. This is accomplished by using vector calculations whereby entire matrices may be added, subtracted, multiplied, divided, or otherwise operated upon. However, even with the increased speeds afforded by performing vector calculations in a vector processing computer system, convolution has traditionally been a serial operation that does not take advantage of the vector processing power. As a result, an efficient, vector processing system may perform multiple tasks using parallel computing and not make use of the parallel calculating capability for convolution operations, thereby slowing the entire system while awaiting the results of a convolution calculation. The diminished processing speed is further exacerbated by the fact that linear processing typically occurs in a part of the computer's central processing unit separate from the vector processor. Consequently, the delays associated with

transferring data between the linear and vector processors further slow the overall process.

[0009] Accordingly, it is desirable to create a system and method for performing convolution in a vector processing computer system that utilizes the parallel calculating capability of the system in a manner so as to make the most efficient use of the computer system.

SUMMARY OF THE INVENTION

[0010] In accordance with the present invention, these objectives are achieved by a system and method that performs convolution in a single channel of a vector processing computer system. This system and method take advantage of the distributive properties of the discrete-time convolution sum by reading in data, buffering data into a given number of data chunks, transposing the data chunks within a matrix to align the first bit of each data chunk, performing the convolution sums on each of the columns of a matrix simultaneously, storing the results from each column's convolution sums as partial solutions, superimposing the results of each column's convolution sums into a single data stream representing an overall solution to be further processed by the computer. According to an embodiment of the invention, the data is transposed and manipulated within a matrix. According to another embodiment of the present invention, one of the data signals or vectors used in the convolution sum is a vector comprising a series of ones. By utilizing a series of ones, a simplification of the overall convolution sum, which is the sum of products is achieved as the operation is reduced to an operation of sums only.

[0011] Further features of the invention and the advantages offered thereby are explained in greater detail hereinafter with reference to specific embodiments illustrated in the accompanying drawings.

0996877 "113001
FOUETT 2896660

BRIEF DESCRIPTION OF THE DRAWINGS

[0012] Figure 1 is an exemplary computer system in which the system and method of the present invention may be employed.

[0013] Figures 2A-2I illustrate a graphical representation of the process of performing a basic convolution sum.

[0014] Figures 3A-3N illustrate graphically the manner in which convolution may be performed by breaking a function up into multiple pieces, as is performed in accordance with an embodiment of the present invention.

[0015] Figure 4 illustrates a specific case of a convolution sum in accordance with an embodiment of the present invention.

[0016] Figure 5 illustrates a specific case of a convolution sum in accordance with an embodiment of the present invention.

[0017] Figures 6A and 6B illustrate the manner in which the data is buffered in a matrix format to perform parallel convolution in accordance with an embodiment of the present invention.

DETAILED DESCRIPTION OF THE PREFERRED EMBODIMENT

[0018] To facilitate an understanding of the principles and features of the present invention, it is explained hereinafter with reference to its implementation in an illustrative embodiment. In particular, the invention is described in the context of a vector processing computer system that performs discrete-time convolution. This may be accomplished, according to one embodiment, by a simplified computation using a vector containing all ones, thereby simplifying the sum-of-products operation associated with convolution to a simple summation. It will be appreciated, however, that this is not the only embodiment in which the invention can be implemented. Rather, it can find utility in a variety of computer

0999687 "113001

configurations utilizing a variety of different signal vectors, as will become apparent from an understanding of the principles which underscore the invention.

[0019] An exemplary computer system of the type in which the present invention can be employed is illustrated in block diagram form in Figure 1. The structure of the computer itself does not form part of the present invention. It is briefly described here for a subsequent understanding of the manner in which the features of the invention cooperate with the structure of the computer.

[0020] Referring to Figure 1, the system includes a computer 100 having a variety of external peripheral devices 108 connected thereto. The computer 100 includes a Central Processing Unit (CPU) 112, a main memory which is typically implemented in the form of Random Access Memory (RAM) 118, a static memory that can comprise a Read Only Memory (ROM) 120, and a permanent storage device, such as a magnetic or optical disk 122. The CPU 112 communicates with each of these forms of memory through an internal bus 114. The peripheral devices 108 include a data entry device such as a keyboard 124, and a pointing or cursor control device 102 such as a mouse, trackball or the like. A display device 104, such as a CRT monitor or an LCD screen, provides a visual display of the information that is processed within the computer, for example the contents of a computer file. A hard copy of the information displayed on the display device 104 can be provided through a printer 106, or similar device. In addition, a scanner may be provided to allow the input and conversion of a paper document into computer processing memory. Each of these external peripheral devices communicates with the CPU 112 by means of one or more input/output ports 110 on the computer. The input/output ports 110 also allow the computer 100 to interact with a local area network server or an external network 128 such as a LAN, WAN, or the Internet 130.

[0021] Computer 100 typically includes an operating system, which controls the allocation and usage of the hardware resources such as memory,

0996637 11004

central processing unit time, disk space, and peripheral devices. In addition to an operating system, the computer 100 may also include various other software programs designed to interface with the CPU 112. Various functionalities are contained within the CPU 112, such as the ability to process data. One of the operations performed by the CPU 112 is the convolution sum used for signal processing which is shown in Equation 2.

[0022] Figures 2A-2I show a graphical representation of the process of calculating the convolution sum shown in Equation 2. Two signals $f[k]$ and $g[k]$ are shown in Figures 2A and 2B, respectively. To facilitate an understanding of the manner in which the functions are processed during convolution, they are expressed in terms of a second parameter m , resulting in the signals $f[m]$ and $g[m]$ shown in Figures 2C and 2D, respectively. In Figure 2E, one of the signals, in this case $g[m]$, is reflected across the y-axis and expressed as $g[-m]$. The reflected signal $g[m]$ is then shifted by varying amounts k until it has been translated over the entire length of the m -axis. Because the convolution is being calculated, the value of k is varied in increments that correspond to the increments between discrete values of each of the function $f[k]$ and $g[k]$ being operated on. At each value of k , the overlapping values of each function are multiplied together and the products summed.

[0023] In the case shown in Figures 2A-2I, however, the first function $f[k]$ is made up of a series of ones. Thus, summing the products of each of the overlapping functions (i.e., $f[m]$ and $g[k-m]$) at each value of k is equivalent to the sum of each overlapping value of the second function $g[k-m]$ for each value of k for which it overlaps the first function $f[m]$. In Figure 2F, the function $g[k-m]$ is shifted by the amount k_1 . Summing the portions of $g[k-m]$ that overlap $f[k]$ when it is shifted by this amount results in a first sum S_1 . In Figure 2G, a second sum S_2 is achieved by shifting the second function $g[k-m]$ by a different amount k_2 and summing the overlapping portions of the second function $g[k-m]$. In Figure 2H,

the situation in which the function $g[k-m]$ is shifted by yet a different amount k_3 , such that there is no overlap between the two functions, is shown. In this case, there is no sum to be performed, as no values of the two functions overlap and thus S_3 is zero. The overall result of the convolution sum is shown in Figure 2I, where the result $y[k]$ is illustrated along the k -axis, and corresponds to cumulation of all sums of the overlapping values of the two functions for each value of k .

[0024] In performing the convolution such as the one shown in Figures 2A-2I, however, there arises a complication as the number of values to sum may be great, and is generally performed as a serial process within computers. When the convolution shown in Figures 2A-2I is performed as a serial process, each value is operated upon in turn within a stream of data. When this stream of data is large, the time required to perform the convolution sum may be great, which may result in slowing other computer processing operations, or other undesirable effects (e.g., distortion of real-time data, etc.).

[0025] In order to speed up the convolution process, it may be implemented in a vector processing system in a manner such that calculations are performed in parallel. This can be accomplished by utilizing the distributive property inherent to the convolution sum. The distributive property of convolutions is shown in Equation 3 below.

$$y[k] = f[k] \otimes (g_1[k] + g_2[k]) = f[k] \otimes g_1[k] + f[k] \otimes g_2[k] = y_1[k] + y_2[k] \quad (3)$$

[0026] In Equation 3, the second function to be convolved $g[k]$ is described as the sum of two components $g_1[k]$ and $g_2[k]$. As shown in Equation 3, the result of convolving $f[k]$ with the sum of two individual signals is actually the same as convolving $f[k]$ with each of the two signals and then adding, or superimposing, the results. This property is useful in performing vector calculations of

0996877-113001

convolution because a large, complex signal may be buffered and divided into a specified number of data chunks and each of these data chunks may be operated upon individually in parallel. In the end, the same result can be obtained by superimposing the results of the operations performed on each of the data chunks separately.

[0027] An example of performing convolution on individual components of a function is shown in Figures 3A-3N, which illustrates the use of the distributive property for performing discrete convolution sums. In Figures 3A and 3B two functions $f[k]$ and $g[k]$ are shown, respectively which are similar to the functions shown in Figures 2A and 2B. The function $g[k]$, shown in Figure 3B, may be divided into multiple parts, hereinafter referred to as data chunks. In Figures 3C and 3D, $g[k]$ has been divided into two chunks $g_1[k]$ and $g_2[k]$, respectively. Each of these two chunks $g_1[k]$ and $g_2[k]$ is operated upon individually in Figures 3E-3H and Figures 3J-3L, respectively. The partial solutions associated with each data chunk are shown in Figures 3I and 3M, and the overall solution, which is a superposition of the partial solutions, is shown in Figure 3N.

[0028] In Figure 3E, the functions $f[k]$ and $g_1[k]$ are expressed in terms of the parameter m and the second function is reflected across the y -axis, yielding $f[m]$ and $g_1[-m]$. As illustrated in Figures 3A-3I, the convolution of the first data chunk of $g[k]$, or $g_1[k]$, is performed as the transposed and reflected version $g_1[k-m]$ is translated across the m -axis by differing amounts k , as shown in Figures 3F, 3G, and 3H. In Figures 3F-3H each of the values of the overlapping portions of $g_1[k-m]$ are summed and the result is plotted in Figure 3I as a first partial solution $y_1[k]$. Figures 3J, 3K, and 3L illustrate the convolution performed on the second data chunk of $g[k]$, or $g_2[k]$, and the result, a second partial solution $y_2[k]$, is illustrated in Figure 3M. Figure 3N illustrates the superposition of the two convolution results of $g_1[k]$ and $g_2[k]$, as the two partial solutions $y_1[k]$ and $y_2[k]$ are added to arrive at the overall solution $y[k]$.

099687-113001

[0029] In the example illustrated in Figures 3A-3N, the first function $f[k]$ is illustrated as a series of seven ones. This is useful as this function reduces the sum of products usually associated with convolution to a simple sum. However, those skilled in the art will recognize that a function having other values may also be used with similar results. Also illustrated in Figures 3A-3N is the importance of correct alignment of the various signals and outputs. For example, the results of the convolution of $f[k]$ with $g_1[k]$ and $f[k]$ with $g_2[k]$ must be properly aligned such that when their values are superimposed the correct result is achieved. As the first partial solution $y_1[k]$ has the combined width of $f[k]$ and $g_1[k]$ as shown in Figure 3E, the two solutions $y_1[k]$ and $y_2[k]$ will overlap. It is important to ensure that the solution $y_2[k]$ is placed in the proper location, which in digital form is a bit location, so that the correct overall solution $y[k]$ is achieved by proper superposition.

[0030] The generalized form of the distributive property of the convolution sum is shown in Equation 4 below.

$$y[k] = f[k] \otimes \sum_{n=1}^N g_n[k] = \sum_{n=1}^N \{f[k] \otimes g_n[k]\} = \sum_{n=1}^N y_n[k] \quad (4)$$

Equation 4 illustrates that the distributive property is shown to work with more than two chunks of data, as multiple partial solutions may be summed (or superimposed) to achieve an overall solution. This property is useful in the present invention, as in a vector computer processing system multiple sets of data may be used simultaneously as multiple vectors may be simultaneously operated upon. In such a system, the processor time saved is at least proportionate to the number of simultaneous calculations that can be performed, and may be greater when data transfer operations are considered.

09996877-113001

[0031] In Equation 4, the parameter N represents the number of chunks that the function $g[k]$ is to be divided into. The value n is used as an index to distinguish the various chunks of the overall function $g[k]$ (i.e., $g_1[k]$, $g_2[k]$, $g_3[k]$, ..., $g_n[k]$, etc.). Equation 4 illustrates that regardless of the number of pieces or data chunks that the overall second function $g[k]$ is broken up into, a first function $f[k]$ may be convolved with each of these data chunks individually and the results (i.e., multiple partial solutions) can then later be superimposed upon each other, or added together, to yield the overall solution or resulting signal.

[0032] In Figure 4, the discrete values of the solution $y[k]$ are shown for the signals shown in Figures 3A and 3B. These values are arrived at by the convolution sum shown in Equation 2. However, in this illustrative example, as the first function $f[k]$ is a specialized function, which is a series of seven ones, the multiplication step usually required for convolution is essentially removed changing the traditional sum of products to a simple sum. One skilled in the art will recognize, however, that this is a special case, and that the present invention need not be limited to such a specialized implementation. As can be seen in Figure 4, the function $g[k]$ is translated such that it overlaps $f[k]$ and the overlapping values of the function are $g[k]$ added to achieve the values of the solution. For example, the first bit of the solution, or the zero bit $y[0]$, corresponds to the first value of the $g[k]$ function, $g[0]$. Subsequent values of the $g[k]$ function are then added to produce subsequent elements of the solution. The number of bits added from the function $g[k]$ is increased for each bit of the solution $y[k]$ until the size limit, or number of elements in the $f[k]$ function (in this instance seven elements) is reached.

[0033] Then, as the function $g[k]$ is translated with respect to the function $f[k]$, the maximum number of seven elements which may overlap the $f[k]$ function remains constant (e.g., as shown for $y[6]$, $y[7]$, and $y[8]$) and the subsequent groups of seven elements are added. This addition of each set of seven elements

009637-11001

continues until the end of the function $g[k]$ is reached. As the end of $g[k]$ reaches the function $f[k]$, element-by-element there is less overlap for each subsequent value of k (i.e., as $g[k]$ is shifted further to the right). As the overlap decreases, so does the length of each partial solution vector $y[k]$, until there is no overlap, where the value of $y[k]$ is 0.

[0034] The first seven values of the solution $y[k]$ (i.e. $y[0]$, $y[1]$, $y[2]$, $y[3]$, $y[4]$, $y[5]$, $y[6]$) correspond to a period known as the ramp-up time. It is during this time when the number of elements to be convolved from the function $g[k]$ is increased for each iteration. This occurs until the maximum overlap is achieved which in the case illustrated in Figure 4 is an overlap of seven elements. For example, during the first iteration $y[0]$ utilizes only one value of the $g[k]$ function (i.e., $g[0]$). Until the number of iterations is equal to the length of $f[k]$ (i.e., seven elements), which is also referred to as the stride length, each subsequent element of $y[k]$ utilizes one additional element of $g[k]$ in a summation than the preceding element of $y[k]$. When the last value in the ramp-up period has been calculated, the number of values of the function $g[k]$ used to calculate the solution bit $y[k]$ remains constant (i.e., seven elements in the case illustrated).

[0035] At the other end of the convolution, when the end of the function $g[k]$ is reached and the overlapping portion between the functions begins to decrease below the stride length, a corresponding ramp-down process occurs, as illustrated in Figure 5. In the example of Figure 5, the parameter N represents the number of elements in the function $g[k]$. During the ramp-down period, the number of values being added decreases from the stride length (i.e., seven in the case illustrated) to zero with each iteration. As can be seen in Figure 5, the length of the overall solution $y[k]$ (i.e., the width of the solution function) is equivalent to the length of the two functions $g[-m]$ and $f[m]$ as shown in Figure 2E with a single value overlapping. That is, the length of the solution $y[k]$ is the length of $g[-m]$, or N , plus the additional six values of $f[m]$ that do not overlap $g[-m]$ (i.e., $N+6$).

09996877-113001

[0036] In order to perform the convolution on the function $g[k]$ in a vectorized manner, the data is read into the computer processor as a standard stream of data, and divided into chunks of data. For instance, each data chunk might comprise eight elements of data. These data chunks can be visualized in matrix form as shown, for example, in Figure 6. In this form, the vector processor can operate upon eight different items of data at a time. To do this efficiently, the matrix is transposed, so that each element at position (i,j) is moved to a new position (j,i) , for all values of i and j . An example of the transposed matrix is shown in Figure 6B. The data chunks are stored in the transposed matrix such that the first bit of each data chunk appears in the first row of the matrix, and successive bits of a data chunk appear in successive rows within a column of the matrix associated with that data chunk. That is, $g[0]$ and $g[8]$ are in the same row as they are the first bit of their respective data chunks. The second bit of each data chunk is distributed in the second row and the third bit in the third row, and so forth. After the data has been arranged into the matrix, as shown for example in Figure 6B, it is then operated upon in the manner described in connection with Figures 4 and 5, as follows.

[0037] Each of the data chunks, which are separated into individual columns within the matrix shown in Figure 6B, are operated upon simultaneously using the distributive property shown in Equation 4. There is no loss due to the need for each of the data chunks to undergo a ramp-up time, as this time period is needed regardless of the signal being convolved, and performing eight ramp-up calculations simultaneously requires no more time than performing the necessary single ramp-up calculation. Equation 5 below shows the relationship of the columns of the matrix shown in Figure 6 to $g[k]$ as a whole.

$$g[k] = \sum_{c=1}^8 \vec{g}_c[k] \quad (5)$$

In the Equation 5 above, $\vec{g}_c[k]$ is the vector stored in column C . Thus, in Equation 5, $g[k]$ is shown as a sum or superposition of all of the column vectors shown in the matrix of Figure 6. Equation 5 indicates that the superposition of all (i.e., eight) of the column vectors of the matrix in Figure 6B yields the function $g[k]$. It should be noted that in performing the superposition of Equation 5, the element indices of each element of $g[k]$ may be retained so that the function shown in Equation 5 acts as a vector superposition rather than a scalar summation.

[0038] The convolution of each of the column vectors shown in Figure 6B yields the individual solution vectors in column form. It will be appreciated by those skilled in the art that the convolution of each of the column vectors shown in Figure 6B may be performed concurrently, or in parallel. Equation 6 below shows the manner in which the column vectors $\vec{y}_c[k]$ of the overall solution matrix $y[k]$ may be calculated.

$$\vec{y}_c[k] = \sum_{r=1}^{M+6} [\vec{g}_c[8c-(9-r))-6] + [\vec{g}_c[8c-(9-r))-5] + [\vec{g}_c[8c-(9-r))-4] + [\vec{g}_c[8c-(9-r))-3] + [\vec{g}_c[8c-(9-r))-2] + [\vec{g}_c[8c-(9-r))-1] + [\vec{g}_c[8c-(9-r)]] \quad (6)$$

[0039] In Equation 6, M represents the maximum number of elements in the column vector, or of rows in the matrix shown in Figure 6, which in this is case eight. This value may vary, however, as will be readily appreciated by those skilled in the art. The term $8c-(9-r)$ is the index of $g[k]$ (i.e., $8c-(9-r)$ is k). The values r and c represent the row and column, respectively, of the matrix shown in Figure 6B from which the element is read. Equation 6 uses a summation of seven elements because, in this specific case, the stride length, or the length of the function $f[k]$ being convolved with $g[k]$ (i.e., the maximum length of the two functions), is seven. However, as will be appreciated by those skilled in the art, this stride length may vary, and the number of terms used in the convolution

summation will vary accordingly. The summation in the case of the matrix shown in Figure 6B will vary between 1 and 14, which corresponds to the total width of the function $f[k]$, and each portion of the function $g[k]$ when reflected and having a single value overlapping $f[k]$, as shown in Figure 3E (i.e., the size of $f[k]$, or the stride length which is 7, plus the size of each column vector $\vec{g}_c[k]$, which is 8, less the number of overlapping values, which is 1).

[0040] The convolution sum shown in Equation 6 corresponds to the operation shown in Figures 4 and 5. That is, the various summations of elements within the chunks of data are summed together. The result is a column vector $\vec{y}_c[k]$ partial solution for each column of data in the matrix shown in Figure 6. Each of the partial solutions may then be superimposed under the principle of distribution, to calculate a final result or overall solution $y[k]$ as shown in Equation 7 below.

$$y[k] = \sum_{c=1}^P \vec{y}_c[k] \quad (7)$$

In Equation 7, the value P represents the maximum number of columns of the matrix containing the column vectors $\vec{g}_c[k]$ of the function $g[k]$, which in the case shown in Figure 6B is eight. This value may vary, however, as will be appreciated by those skilled in the art.

[0041] Because of the ability to superimpose the results of multiple convolution sums, a vector processing system may simultaneously perform the convolution sum operation on entire rows of the matrix shown in Figure 6B according to Equation 6 (i.e., all column vectors may be operated upon simultaneously). This creates an answer matrix which contains the individual solution column vectors $\vec{y}_c[k]$ that can then be summed, or superimposed,

[0044] It will be appreciated by those of ordinary skill in the art that the present invention can be embodied in other specific forms without departing from the spirit or essential characteristics thereof. For example, the invention has been described for an illustrative case in which one of the convolved functions is a vector of seven bits which each have a value of 1. However, the present invention can also be used with vectors of varying sizes having elements of various values. It is conceivable as the computing power increases, the size of the data chunks

with which calculations are performed may be increased. Also, the size of the matrix containing the various vectors which are used in the convolution may also be increased according to the computing power of the processor being used. It is also possible, that the length and size of the vector with which a signal is convolved may conform to a specific, desired application or a specific signal present in a particular application.

[0045] The presently disclosed embodiments, are, therefore, considered in all respects to be illustrative and not restrictive. The scope of the invention is indicated by the independent claims, rather than the foregoing description, and all changes that come within the meaning and range of equivalents thereof are intended to be embraced therein.

099687 113091